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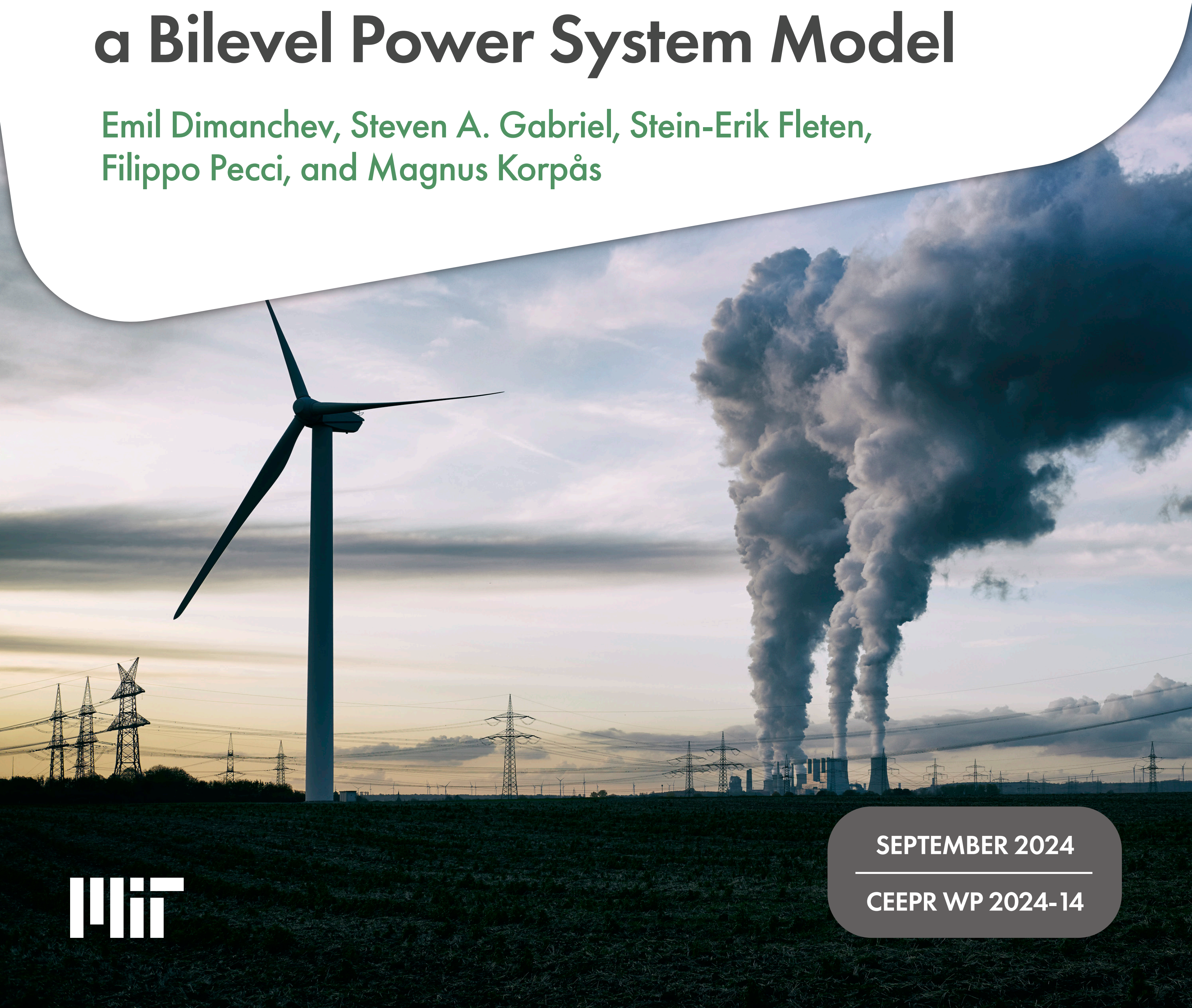

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Choosing climate policies in a second-best world with incomplete markets: insights from a bilevel power system model

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Abstract

Climate policy makers aim to accelerate investments in clean energy. A challenge facing investors in liberalized electricity markets is the incompleteness of long-term markets, which can leave investors exposed to unhedged risk. We consider how governments should choose renewable subsidies and carbon taxes in such markets. For this purpose, we develop a new game theoretic, bilevel model that explicitly captures optimal policy choices in anticipation of electricity market behavior. This allows us to endogenize the optimal climate policy decisions of a government maximizing social welfare in a market with risk-averse decision makers. We present an illustrative case study for a power system with a traditional gas technology, variable renewables, storage, and a clean dispatchable technology under demand and gas price uncertainty. We observe that optimal investment tax credits and carbon prices are both higher when long-term markets are missing than when markets are complete. Perhaps surprisingly, investment tax credits are more cost-effective than a carbon tax in some cases where risk markets are missing. This occurs because, by increasing investment in renewables, subsidies can reduce exposure to unhedged risk. A policy mix combining both instruments is the most cost-effective strategy across our experiments.

Nomenclature

Indices and Sets

$s \in S$ Demand scenarios

$f \in F$ Fuel cost scenarios

$t \in T$ Time steps (hours)

$l \in L$ Load segments

$r \in R$ Technology resources

$G \subset R$ Generation technologies

$O \subset R$ $(O \cap G = \emptyset)$ Storage technologies

Parameters

D_{ts} Demand (MWh)

N_l^{DR} Maximum demand reduction (fraction)

C_{rf}^{var} Variable cost (\$/MWh)

C_r^{inv} Investment cost (\$/MW)

C_l^{DR} Load shedding cost (\$/MWh)

W_t Weight of representative time period (fraction)

A_{rt} Availability of generation resource (fraction)

F^{ch} Charging efficiency (fraction)

F^{dch} Discharging efficiency (fraction)

N_r^s Power to energy ratio for storage technologies (fraction)

Ψ Probability level used to parameterize risk aversion (fraction)

Ω Weight for risk aversion (fraction)

P_{sf} Probability of demand s and gas price f (fraction)

E_r^{co2} Emissions intensity (tCO_2/MWh)

$\bar{E}^{co2}$ Government's emissions target (tCO_2)

Decision variables - representative investor

x_r Capacity (MW)

$\tilde{\zeta}$ Value at Risk (VaR) for representative investor ($)

$\tilde{u}_{sf}$ Loss relative to VaR for representative investor ($)

Decision variables - ISO

g_{rtsf} Generation (MWh)

y_{ltsf} Load shedding (MWh)

e_{rtsf} Energy stored, i.e., state of charge (MWh)

z^{ch}_{rtsf} Charging of storage technology (MWh)

z^{dch}_{rtsf} Discharging from storage technology (MWh)

Decision variables - government

σ_r Investment Tax Credit (fraction)

c^{tax} Carbon tax ($/t$CO_2$)

ζ^{gov} VaR for government ($)

u^{gov}_{sf} Loss relative to VaR for government ($)

Additional decision variables

ζ^{cp} VaR for complete market model ($)

u^{cp}_{sf} Loss relative to VaR for complete market model ($)

Dual variables

λ_{tsf} Price of electricity ($/MWh)

μ_{rtsf} Capacity value ($/MW)

$\phi^{soc}_{rtsf}, \phi^{cap}_{rtsf}, \phi^{c}_{rtsf}, \phi^{d}_{rtsf}, \phi^{bal}_{rtsf}, \xi^{d}_{rtsf}$ Dual variables corresponding to storage constraints

$\tilde{\theta}_{sf}$ Risk-adjusted probability for representative investor (fraction)

θ^{gov}_{sf} Risk-adjusted probability for government agent (fraction)

θ^{cp}_{sf} Risk-adjusted probability for complete market model (fraction)

Auxiliary variables

θ^{Z}_{rsf} Binary indicating whether scenario (s, f) is in the CVaR tail

ν_{rsf} Revenues in CVaR tail ($/MW)

h_{rsf} Revenues outside of CVaR tail ($/MW)

1 Introduction

To meet climate targets, governments must incentivize investments in clean electricity technologies. Policy makers at the U.S. federal level primarily use Investment Tax Credits (ITCs) for this purpose. Carbon pricing has also been implemented by policy makers in other jurisdictions, including at the U.S. state level as well as in Canada and the European Union. The design and relative merits of these instruments are subject to continuing debate in the academic literature. In this paper, we consider how the answers to such questions depend on electricity market risks caused by inefficiencies in risk allocation.

A salient feature of liberalized electricity markets is that producers and consumers bear uninsured risks. Risk matters because decision makers generally exhibit risk aversion. How much risk they face depends on their ability to hedge risk using, for example, long-term electricity contracts. In the theoretical first-best[1] world often assumed in energy policy analyses (Scott et al., 2020, e.g.), risk markets are complete, which means that decision makers can trade contracts that insure them against any possible future. In reality however, risk trading in electricity markets is far from complete. This is exemplified by the low liquidity of markets for long-term contracts (ACER, 2022; Batlle et al., 2023), and is also known as the missing market problem (Newbery, 2016). Proposed reasons for market incompleteness include asymmetric information and transaction costs (Radner, 1970; Arrow and Lind, 1970), and electricity industry characteristics disincentivizing consumer procurement of long-term contracts (Wolak, 2013; Batlle et al., 2023). Previous research has shown that the missing market problem can decrease power system reliability (Mays et al., 2022) and increase power system emissions (Dimanchev et al., 2024).

The incompleteness of risk markets complicates climate policy design. In theory, the optimal government strategy is a policy mix combining a first-best solution to completing risk markets with a first-best climate policy instrument (Tinbergen, 1952; Wolak, 2022; Waidelich et al., 2023; Haas and Kempa, 2023). Yet in practice, such first-best solutions may not be readily available for either of these market inefficiencies. First, in the case of climate change, the first-best carbon pricing policy faces political economy constraints (Jenkins, 2014; Rabe, 2018). Second, completing risk markets may be infeasible within the short time frame within which governments aim to mobilize large amounts of capital for the clean energy transition. For example, the International Energy Agency's Net Zero Scenario envisions that global energy sector investment increases by 80% by 2030 relative to 2022 (IEA, 2023).

Therefore, a problem facing climate policy makers is how to choose and design available policy instruments for a second-best world with incomplete long-term markets. This challenge raises the following questions, which motivate this paper. First, how do optimal levels of common climate policies change with incomplete long-term markets? The policies

[1] Throughout the paper, we refer to a "first-best" economy as one in which there are no market failures except for the climate change externality, in line with prior usage (Goulder et al., 1999). Accordingly, a "second-best" economy is one in which there is an additional market inefficiency, which in our case is an incompleteness of risk markets. When we refer to a first-best policy, we mean the policy that addresses a given market failure in the most efficient way.

we focus on are renewable ITC subsidies and carbon pricing. Second, how does market incompleteness impact the relative cost-effectiveness of different instruments?

We develop a new method for addressing these questions. Through an illustrative analysis, we also derive preliminary insights as to the direction in which market incompleteness may change instruments' optimal levels (first question) and their cost-effectiveness under market incompleteness (second question).

Previous literature used analytical models to explore the first question raised here with regard to carbon pricing (Hoffmann et al., 2017; Newbery, 2018; Heider and Inderst, 2022; Haas and Kempa, 2023; Döttling and Rola-Janicka, 2023) and renewable subsidies (Lehmann and Söderholm, 2018; Nagy et al., 2023). However, analytical models greatly simplify important technical features of power systems such as renewable variability and chronological energy storage operation. For this reason electricity systems are often studied using numerical generation expansion models. We take this approach but the purpose of our paper requires us to address a limitation in such models.

Numerical generation expansion models treat policy parameters such as ITC subsidies and carbon taxes as exogenous. This makes it difficult to model the optimal levels of these instruments. This has led to recent calls for new power system models that endogenize policy choices (Siddiqui et al., 2023). An increasingly popular method for endogenous policy modeling is bilevel programming (Siddiqui et al., 2023). This approach draws on game theory to represent the sequential nature of government-market interactions. Bilevel models feature an "upper-level" decision maker (e.g., a government choosing optimal policies) acting in anticipation of choices made by "lower-level" agents (e.g., electricity market participants) (Abapour et al., 2020; Wogrin et al., 2020). In game theoretic terms, this framework is known as a Stackelberg game between a "leader" agent at the upper level and one or more "follower" agents at the lower level. Here, we develop a new bilevel model that combines optimal climate policy decisions, as an upper-level problem, with power market investment and operating decisions, as a lower-level problem.

Bilevel models for policy design in power systems have been introduced in recent research (Siddiqui et al., 2016; Pineda et al., 2018; Tanaka et al., 2022; Billimoria et al., 2022; Bichuch et al., 2023). However, this literature has omitted energy storage and only one study has modeled variable renewables with more than a few time periods (Pineda et al., 2018). This can be explained in large part by the computational challenges inherent to bilevel programming (Wogrin et al., 2020). The model we introduce addresses these challenges to a degree, allowing us to capture the impacts of renewable variability and to model chronological energy storage operation. We demonstrate the model for a case study with 336 operational time periods, which exceeds the temporal resolution of commonly used energy system models (Nahmmacher et al., 2016). Our methodology also allows us to capture, in an illustrative way, risk aversion and the incompleteness of risk trading in liberalized power markets.

The introduced bilevel modeling approach extends the decision support toolkit available for climate policy design in several ways. First, by endogenizing optimal subsidies, our framework can shed light on how subsidies should be designed. Though subsidies are widely used by climate policy makers, there has been relatively little analytical work on how they can deliver the biggest "bang for the buck" (Newell et al., 2019). Instead, climate policy analyses typically focus on modeling optimal carbon prices rather than subsidies (Pollitt et al., 2024). Second, our bilevel framework allows the co-optimization of multiple policy instruments (i.e., a policy mix), as our analysis demonstrates. Third, bilevel modeling offers flexibility in framing a variety of policy maker objectives.

For our analysis, we conceptualize an optimal policy (upper-level) problem as choosing a policy that drives power system emissions to a pre-defined emissions target[2] at the lowest overall risk-adjusted cost. While this leaves out a variety of important criteria other than cost-effectiveness, the methodology we develop makes it possible to introduce such criteria in future research.

To address our first question, we use our modeling framework to perform exploratory analysis of the directional impact of the missing market problem. For this purpose, we construct two bilevel models representing first a "missing market" case where electricity investors cannot trade long-term contracts with consumers, and, second, a benchmark "complete market" case with complete trading of long-term contracts. To address our second question, we compare the relative cost-effectiveness of different instruments in our missing market case to their relative cost-effectiveness in the complete market case.

Our results show that optimal ITC subsidies and carbon taxes are higher when long-term markets are missing than when they are complete. A more striking result is that missing long-term markets can make ITC subsidies more cost-effective than carbon pricing in some cases. This is contrary to the classical economic prescription of carbon pricing as the most cost-effective policy, but consistent with the theory of second best, which suggests that the optimal policy in an efficient economy (a.k.a., first-best) may not be optimal in an economy subject to a market failure (a.k.a., second-best) (Lipsey and Lancaster, 1956). Our results showcase that climate policy can benefit a second-best power system with incomplete risk markets by mitigating unhedged risk.

2 Methods

We formulate two versions of our model. First, our main model version introduced below in Section 2.1 represents a power system without long-term markets. We use this model for our "missing market" case, which is the focus of this paper. Second, we construct a benchmark model with complete long-term markets, which is described later in Section 2.2.

[2]In contrast to our approach, some previous literature endogenizes the emissions target by equating marginal abatement costs with marginal benefits (Tanaka et al., 2022, e.g.). However, as Stern et al. (2022) point out, governments have generally adopted what the authors refer to as a "guardrail approach", which consists of a politically agreed climate target and a subsequent process of selecting the policies that best meet that target.

2.1 Bilevel model with missing long-term markets

Figure 1 illustrates the structure of our main bilevel model. The upper level represents the government's problem of choosing optimal climate policies in anticipation of the investment and operating decisions made by power market agents. The government problem is formulated in Section 2.1.2.

The lower level of our model represents the investment and operating decisions in an energy-only, perfectly competitive electricity market with no long-term contracts between investors and consumers. As shown in previous work, this power market can be modeled as an equilibrium between risk-averse investors and an Independent System Operator (ISO) (Dimanchev et al., 2024). We use the same formulation here but extend it to include policy parameters and flexible demand, as described in the following section.

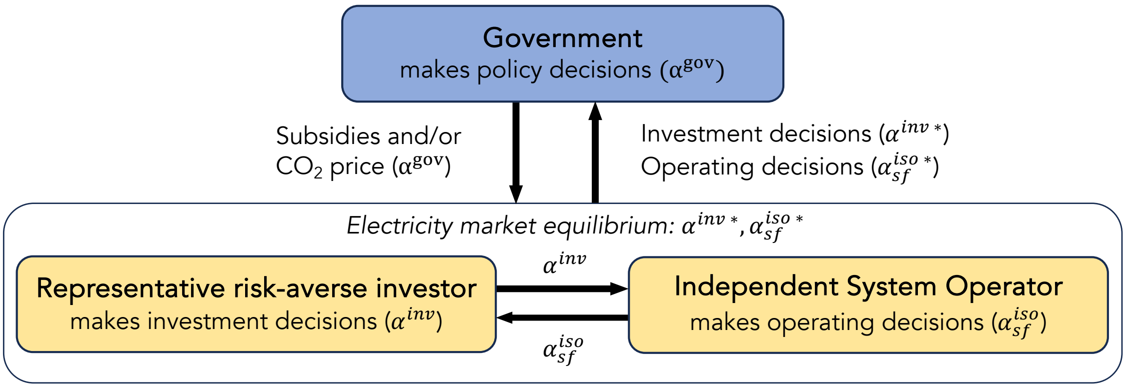

Figure 1: Bilevel power system model framework

2.1.1 Risk-averse power market model with missing risk trading (lower level)

The power market is represented as an equilibrium problem comprising the investment decisions of risk-averse investors and the operating decisions of an Independent System Operator (ISO). This formulation builds on the stochastic risk-averse equilibrium approach introduced by Ehrenmann and Smeers (2011). Equilibrium modeling departs from the traditional method of modeling a power market as a central planning cost minimization problem. The traditional framework assumes complete risk trading between agents (Ralph and Smeers, 2015; Munoz et al., 2017), as it implicitly aggregates agents into a single central planner. In contrast, our model disaggregates investment decision making (contained in the investor problem) from generation and consumption decisions (contained in the ISO problem). The model thus effectively represents a market with no risk trading (i.e., long-term contracts) between investors and consumers (Dimanchev et al., 2024). It is worth noting, however, that our model is consistent with the traditional approach when agents are risk-neutral (risk neutrality makes risk trading irrelevant)[3].

[3]More formally, the two approaches yield the same result when $\Omega = 1$, as expected since the optimality conditions of the risk-neutral equilibrium problem are equivalent to the optimality conditions of the

2.1.1.1 Risk-averse investment problem

Investors decide how much capacity x_r to deploy of each technology $r \in R$ with the objective of maximizing profit subject to risk preferences modeled using the commonly employed Conditional Value at Risk (CVaR) function (Rockafellar and Uryasev, 2002). The problem formulation was previously introduced in Dimanchev et al. (2024). The version shown here additionally includes the ITC subsidy, σ_r, which represents the fraction of the investment cost C_r^{inv} to be subsidized by the government. Note that the ITCs can be equivalently interpreted as investment grants. Investors' marginal revenues[4] in each scenario are denoted by π_{rsf} (defined below), where s indexes demand scenarios and f indexes gas price scenarios.

Investors are modeled with one representative price-taking investor agent that invests in all technologies[5]. As shown by the objective function (1a) below, the investor maximizes a weighted combination of expected profits (represented by the first bracketed term) and the CVaR of the profit distribution (represented by the second bracketed term). The CVaR is modeled as in prior work with constraint (1b), which sets the CVaR to the expected value of the Ψ-worst tail of the profit distribution. In practical terms, the investor is placing additional weight on unfavorable scenarios. The investor's problem is a linear program when considered on its own, as the subsidy term σ_r and the revenue term π_{rsf} are parameters for the investor.

$$\max_{\alpha^{inv}} \ \Omega\Bigg[\sum_s\sum_f P_{sf}\sum_r \pi_{rsf}x_r - (1-\sigma_r)C_r^{inv}x_r\Bigg] + (1-\Omega)\Bigg[\tilde{\zeta} - \frac{1}{\Psi}\sum_s\sum_f P_{sf}\tilde{u}_{sf}\Bigg] \tag{1a}$$

$$\text{s.t.} \quad \tilde{u}_{sf} \geq \tilde{\zeta} - \sum_r \left[\pi_{rsf}x_r - (1-\sigma_r)C_r^{inv}x_r\right] \quad \forall\, s \in S, f \in F \ \ (\tilde{\theta}_{sf}) \tag{1b}$$

$$x_r \geq 0 \quad \forall\, r \in R \tag{1c}$$

$$\tilde{u}_{sf} \geq 0 \quad \forall\, s \in S, f \in F \tag{1d}$$

$$\tilde{\zeta} \in \mathbb{R} \tag{1e}$$

where set α^{inv} contains the variables $(x_r, \tilde{\zeta}, \tilde{u}_{sf})$. π_{rsf} represent revenues from the power market. These are defined as follows for generation and storage resource respectively:

$$\forall\, r \in G,\ \pi_{rsf} := \sum_t \mu_{rtsf}A_{rt}$$

corresponding central planning cost-minimization problem, as discussed in Dimanchev et al. (2024)

[4]This refers to revenues per unit of capacity.

[5]This formulation offers computational advantages. A comparison of this approach to an alternative where different investor agents are defined for each technology was provided in Dimanchev et al. (2024). By using a representative investor, we assume risk sharing between individual technologies; in contrast formulating an investor agent for each technology would capture a lack of risk trading between technologies.

$$\forall\, r \in O,\ \pi_{rsf} := \sum_t \left[\frac{1}{N_r^s} \phi_{rtsf}^{cap} + \phi_{rtsf}^{c} + \phi_{rtsf}^{d} + \phi_{rtsf}^{bal} \right]$$

As shown above, π_{rsf} is a function of the dual values associated with the capacity constraints in the power system dispatch problem solved by the ISO, which is introduced next. Thus π_{rsf} captures the value of capacity, which is equal to the revenues (after operating costs) that generators and storage resources would earn from selling energy on the wholesale market (Dimanchev et al., 2024).

2.1.1.2 Independent System Operator (ISO) problem

The ISO agent dispatches the resources built by investors to meet electricity demand in each scenario (s, f) in the least-cost way, subject to engineering constraints. The formulation was previously introduced in Dimanchev et al. (2024). Here, we extend the model to include the government policies we consider, and include flexible demand. The policy of relevance to the ISO problem is the carbon tax, denoted, c^{tax}, which enters as an additional variable cost in the ISO objective function. Flexible demand is modeled following the approach used in the GenX model (MIT Energy Initiative and Princeton University ZERO lab, 2023). This is done by using a piece-wise linear combination of demand segments, indexed by l where demand in segment l is reduced by y_{ltsf} at a cost of C_l^{DR}. The non-served energy y_{ltsf} for each segment l is constrained to be a fraction N_l^{DR} of the total demand by (2c), where parameter N_l^{DR} is exogenously determined. The ISO's optimization problem, which is a linear program, follows.

$$\min_{\alpha^{iso}} \sum_t W_t \sum_r C_{rf}^{var} g_{rtsf} + \sum_t W_t \sum_r E_r^{co2} c^{tax} g_{rtsf}$$
$$+ \sum_t W_t \sum_l C_l^{DR} y_{ltsf} \quad \forall\, s \in S, f \in F \tag{2a}$$

$$\text{s.t.} \quad \sum_r^{|G|} g_{rtsf} + \sum_r^{|O|} \left[z_{rtsf}^{dch} - z_{rtsf}^{ch} \right] + \sum_l y_{ltsf} = D_{ts} \forall\, t \in T, s \in S, f \in F \quad (\lambda_{tsf}) \tag{2b}$$

$$y_{ltsf} \leq N_l^{DR} D_{ts} \quad \forall\, l \in L, t \in T, s \in S, f \in F \quad (\gamma_{ltsf}) \tag{2c}$$

$$g_{rtsf} \leq x_r A_{rt} \quad \forall\, r \in G, t \in T, s \in S, f \in F \quad (\mu_{rtsf}) \tag{2d}$$

$$e_{r1sf} = e_{r|T|sf} - \frac{1}{F^{dch}} z_{r1sf}^{dch} + F^{ch} z_{r1sf}^{ch} \quad \forall\, r \in O, s \in S, f \in F \quad (\phi_{r1sf}^{soc}) \tag{2e}$$

$$e_{rtsf} = e_{rt-1sf} - \frac{1}{F^{dch}} z_{rtsf}^{dch} + F^{ch} z_{rtsf}^{ch}$$
$$\forall\, r \in O, t \in \{2, 3, ..., |T|\}, s \in S, f \in F \quad (\phi_{rtsf}^{soc}) \tag{2f}$$

$$e_{rtsf} \leq \frac{1}{N_r} x_r \quad \forall\, r \in O, t \in T, s \in S, f \in F \quad (\phi_{rtsf}^{cap}) \tag{2g}$$

$$z_{rtsf}^{ch} \leq x_r \quad \forall\, r \in O, t \in T, s \in S, f \in F \quad (\phi_{rtsf}^{c}) \tag{2h}$$

$$z_{r1sf}^{dch} \leq e_{r|T|sf} \quad \forall\, r \in O, s \in S, f \in F \quad (\xi_{r1sf}^{d}) \tag{2i}$$

$$z^{dch}_{rtsf} \leq e_{rt-1sf} \quad \forall\, r \in O, t \in \{2, 3, ..., |T|\}, s \in S, f \in F \qquad (\xi^{d}_{rtsf}) \quad (2j)$$

$$z^{dch}_{rtsf} \leq x_r \quad \forall\, r \in O, t \in T, s \in S, f \in F \qquad (\phi^{d}_{rtsf}) \quad (2k)$$

$$z^{dch}_{rtsf} + z^{ch}_{rtsf} \leq x_r \quad \forall\, r \in O, t \in T, s \in S, f \in F \qquad (\phi^{bal}_{rtsf}) \quad (2l)$$

$$g_{rtsf} \geq 0 \quad \forall\, r \in G, t \in T, s \in S, f \in F \quad (2m)$$

$$e_{rtsf}, z^{ch}_{rtsf}, z^{dch}_{rtsf} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \quad (2n)$$

$$y_{ltsf} \geq 0 \quad \forall\, l \in L, t \in T, s \in S, f \in F \quad (2o)$$

where α^{iso} is the set of the decision variables $(g_{rtsf}, y_{ltsf}, z^{ch}_{rtsf}, z^{dch}_{rtsf}, e_{rtsf})$. The objective function minimizes the fuel and variable operating and maintenance costs, C^{var}_{rf}, associated with generation g_{rtsf} (first term), carbon tax costs (second term), and the costs of load shedding y_{ltsf} (third term). (2b) represents the power balance constraint; (2b) constrains generation by the available capacity; Finally, (2e)-(2l) represent energy storage constraints following the GenX model (MIT Energy Initiative and Princeton University ZERO lab, 2023). (2e) and (2f) are classical state of charge accounting equations that wrap the first and last periods. The remaining storage constraints (2g)-(2l) ensure that the state of charge, charging, and discharging do not exceed the energy and power capacities of the battery, while allowing for simultaneous charging and discharging, as in the GenX model.

2.1.2 Government problem (upper level)

We conceptualize the government's problem as aiming to maximize social welfare while meeting a climate policy target. Note that the welfare maximizing equilibrium in a market with risk-averse agents is equivalent in our context to the optimal decisions of a cost-minimizing, risk-averse central planner (Ralph and Smeers, 2015; Munoz et al., 2017). Thus, we formulate the government's objective function (3a) as that of minimizing risk-adjusted system costs, in the mold of previously developed risk-averse power system planning models (Munoz et al., 2017). The government's objective encompasses total investment costs and operating costs (which comprise generation and load shedding costs). The operating costs are modeled as a weighted combination of expected costs (the first bracketed term) and the CVaR (the second bracketed term). This leads to the following linear program.

$$
\begin{aligned}
\min_{\alpha^{gov}} \quad & \sum_r C_r^{inv} x_r + \Omega\Big[\sum_s \sum_f P_{sf} \sum_t W_t \Big[\sum_r C_{rf}^{var} g_{rtsf} + \sum_l C_l^{DR} y_{ltsf}\Big]\Big] \\
& + (1-\Omega)\Big[\zeta^{gov} + \frac{1}{\Psi}\sum_s \sum_f P_{sf} u_{sf}^{gov}\Big] && (3a) \\
\text{s.t.} \quad & \sum_r \sum_t E_r^{co2} g_{rtsf} \leq \bar{E}^{co2} \quad \forall\, s \in S, f \in F && (3b) \\
& u_{sf}^{gov} \geq 0 \quad \forall\, s \in S, f \in F && (3c) \\
& \zeta^{gov} \in \mathbb{R} && (3d) \\
& u_{sf}^{gov} \geq \sum_t W_t \sum_r g_{rtsf} C_{rf}^{var} + \sum_t W_t \sum_l C_l^{DR} y_{ltsf} - \zeta^{gov} \\
& \forall\, s \in S, f \in F \ (\theta_{sf}^{gov}) && (3e) \\
& \sigma_r \in [0,1], \ c^{tax} \geq 0 && (3f)
\end{aligned}
$$

where set $\alpha^{gov} = (\sigma_r, c^{tax}, u_{sf}^{gov}, \zeta^{gov})$ contains all decision variables, which include the policy instruments, namely the ITCs (equivalently interpretable as investment grants), σ_r, and the carbon tax, c^{tax}, as well as the auxiliary variable used to model risk aversion u_{sf}^{gov} and ζ^{gov}.

The government's CVaR represents the expected cost in the Ψ-worst tail of the distribution of operating costs[6]. The CVaR is modeled via (3c)-(3e), which follow the standard approach (Rockafellar and Uryasev, 2002). As the government's objective is meant to reflect the risk aversion of market participants, it uses the same risk aversion parameters, Ω and Ψ. We note that our treatment of risk is simplified because it omits risk sharing between the power market and the broader economy. The government and the power market agents are concerned with power system outcomes independently of how these outcomes correlate with other economic events. In practice, broader risk sharing allows for some degree of diversification that would reduce (though, given the incompleteness of capital markets, not eliminate) agents' risk exposure.

The government's climate target is modeled as an emissions constraint in expression (3b). This target is based on power system emissions (the left-hand side of the constraint), which are a function of the decisions made by power market agents; namely, the generation dispatch g_{rtsf} decided by the ISO. The government can influence the behavior of the power market agents through the available policy instruments, which entail choosing subsidies σ_r and/or a carbon tax c^{tax}. In this way, we deliberately depart from the traditional approach to modeling climate policy, which is to impose an emissions constraint directly on the decisions of power market agents (i.e., placing (3b) in the ISO's dispatch problem (2)). The traditional method effectively represents the implementation of a cap-and-trade system. In contrast, we are interested in how the government can reach a given CO_2 target using other policy instruments. It is worth noting that in some special cases,

[6] This differs from the CVaR of the investor agent modeled in (1), which represents the Ψ-worst tail of the distribution of investor profits.

our method is equivalent to the traditional approach; namely, the optimal carbon tax c^{tax} is equivalent to the dual of cap-and-trade constraint in a deterministic setting as is to be expected.

The cost of the carbon tax is not included in the operating costs (second bracketed term in (3a)). This is because, from the government's perspective, any tax paid by generators is equal to government revenues. Similarly, the government considers the total investment cost, rather than the investment cost after the ITC as in the case of investors.

2.1.3 Solution strategy

The solve the bilevel model comprised of problems (1), (2), and (3), we take the common approach of converting it into a single-level optimization problem (Gabriel et al., 2013; Wogrin et al., 2020), which can be solved with off-the-shelf solvers. For this purpose, we reformulate the investor and ISO optimization problems (i.e., problems (1), (2)) into a set of necessary and sufficient conditions, which are later combined with the government's optimization problem in Section 2.1.6. We derive necessary and sufficient conditions for the investor problem (1) and ISO problem (2) following the approach introduced in Dimanchev et al. (2024). This method converts each optimization problem into its primal-dual form, which comprises the primal constraints, dual constraints, and strong duality condition (Ruiz et al., 2012; Wogrin et al., 2020, e.g.). These conditions are necessary and sufficient because both the investor problem, (1), and ISO problem, (2), are linear programs when considered on their own.

2.1.4 Primal dual reformulation of lower-level problem

The following conditions are necessary and sufficient for the optimal solution of the investor optimization problem (1). This was previously shown in Dimanchev et al. (2024). Expression (4a) refers to the strong duality condition; expressions (4b)-(4j) ensure dual feasibility, and (4k) refers to the investor problem's primal constraints. Note that the formulation relies on a technique introduced in Dimanchev et al. (2024), which facilitates computational tractability by replacing the dual variable $\tilde{\theta}_{sf}$ with the binary θ^Z_{sf} and by introducing the auxiliary variables ν_{rsf} and h_{rsf}.

$$\Omega\Big[\sum_s\sum_f P_{sf}\sum_r \pi_{rsf}x_r - \sum_r(1-\sigma_r)C^{inv}_r x_r\Big] + (1-\Omega)\Big[\tilde{\zeta}_r - \frac{1}{\Psi}\sum_s\sum_f P_{sf}u_{rsf}\Big] = 0 \quad (4a)$$

$$\theta^Z_{rsf} \in \{0,1\} \quad \forall\, r\in R, s\in S, f\in F \quad (4b)$$

$$\frac{1}{\Psi}P_{sf} - \frac{1}{N^{cvar}}\theta^Z_{sf} \geq 0 \quad \forall\, r\in R, s\in S, f\in F \quad (4c)$$

$$\sum_s \sum_f \frac{1}{N^{cvar}} \theta^Z_{sf} = 1 \quad \forall\, r \in R \tag{4d}$$

$$\nu_{rsf} \geq 0 \quad \forall\, r \in R, s \in S, f \in F \tag{4e}$$

$$h_{rsf} \geq 0 \quad \forall\, r \in R, s \in S, f \in F \tag{4f}$$

$$\nu_{rsf} \leq M\theta^Z_{rsf} \quad \forall\, r \in R, s \in S, f \in F \tag{4g}$$

$$h_{rsf} \leq M(1 - \theta^Z_{rsf}) \quad \forall\, r \in R, s \in S, f \in F \tag{4h}$$

$$\nu_{rsf} + h_{rsf} = \frac{1}{N^{cvar}} \pi_{rsf} \quad \forall\, r \in R, s \in S, f \in F \tag{4i}$$

$$(1 - \sigma_r)C^{inv}_r - \Omega \sum_s \sum_f P_{sf}\pi_{rsf} - (1 - \Omega) \sum_s \sum_f \nu_{rsf} \geq 0 \quad \forall\, r \in R \tag{4j}$$

$$(1b) - (1e) \ \big[\text{Primal investor constraints}\big] \tag{4k}$$

Next, we show the ISO's necessary and sufficient primal-dual conditions. These are derived as shown previously (Dimanchev et al., 2024). (5a) is the strong duality condition; expressions (5b)-(5k) represent the dual feasibility constraints; and (5l) represents the primal feasibility constraints. The extension to these conditions that we make in this paper is the derivation of the relevant policy and flexible demand expressions. With regard to flexible demand, we note that the constraint (2c), newly introduced relative to Dimanchev et al. (2024), leads to an additional term at the end of the strong duality condition (5a).

$$\sum_t W_t \sum_r C^{var}_{rf} g_{rtsf} + \sum_t W_t \sum_r E^{co2}_r c^{tax} g_{rtsf} + \sum_t W_t \sum_l C^{DR}_l y_{ltsf} =$$
$$\sum_t \lambda_t D_t - \sum_r \pi_{rsf} x_r - \sum_t \sum_l N^{DR}_l D_{ts} \gamma_{ltsf} \quad \forall\, s \in S, f \in F \tag{5a}$$

$$\lambda_{tsf} \in \mathbb{R} \quad \forall\, t \in T, s \in S, f \in F \tag{5b}$$

$$\mu_{rtsf} \geq 0 \quad \forall\, r \in G, t \in T, s \in S, f \in F \tag{5c}$$

$$\phi^{soc}_{rtsf} \in \mathbb{R} \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{5d}$$

$$\phi^{cap}_{rtsf}, \phi^{c}_{rtsf}, \phi^{d}_{rtsf}, \phi^{bal}_{rtsf}, \xi^{d}_{rtsf} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{5e}$$

$$W_t C^{var}_{rf} - \lambda_{tsf} + W_t c^{tax} E^{co2}_r + \mu_{rtsf} \geq 0 \quad \forall\, r \in G, t \in T, s \in S, f \in F \tag{5f}$$

$$W_t C^{DR}_l + \gamma_{ltsf} - \lambda_{tsf} \geq 0 \quad \forall\, l \in L, t \in T, s \in S, f \in F \tag{5g}$$

$$\phi^{soc}_{rtsf} - \phi^{soc}_{rt+1sf} + \phi^{cap}_{rtsf} - \xi^{d}_{rt+1sf} \geq 0 \quad \forall\, r \in O, t \in \{1, 2, ..., |T| - 1\}, s \in S, f \in F \tag{5h}$$

$$\phi^{soc}_{r|T|sf} - \phi^{soc}_{r1sf} + \phi^{cap}_{r|T|sf} - \xi^{d}_{r1sf} \geq 0 \quad \forall\, r \in O, s \in S, f \in F \tag{5i}$$

$$-F^{ch}\phi^{soc}_{rtsf} + \phi^{c}_{rtsf} + F^{ch}\phi^{bal}_{rtsf} + \lambda_{tsf} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{5j}$$

$$\frac{1}{F^{dch}}\phi^{soc}_{rtsf} + \phi^{d}_{rtsf} + \xi^{d}_{rtsf} + \frac{1}{F^{dch}}\phi^{bal}_{rtsf} - \lambda_{tsf} \geq 0 \quad \forall\, r \in O, t \in T, s \in S, f \in F \tag{5k}$$

$$(2b) - (2o) \ \big[\text{Primal dispatch constraints}\big] \tag{5l}$$

2.1.5 Reformulation of non-convex policy expressions

To improve the computational tractability of our model, we address non-convexities created by the bilinear terms $c^{tax}g_{rstf}$ in (5a), and the bilinear terms $\sigma_r x_r$ in (4a) and (1b). We linearize these terms by using a binary expansion technique (Wogrin et al., 2013). Consider first the terms $c^{tax}g_{rstf}$. The tax variable c^{tax} can be discretized using the following constraints, where Δ^{tax} is an exogenous step size for the tax level, $k \in K$ indexes discretization intervals, and z_k are auxiliary binaries.

$$z_k \in \{0,1\} \quad \forall\, k \in K \tag{6a}$$

$$0 \leq \hat{g_{ksf}} \leq z_k M^{tax} \quad \forall\, k \in K, s \in S, f \in F \tag{6b}$$

$$0 \leq \sum_t W_t E_r^{co2} g_{rtsf} - \hat{g_{ksf}} \leq (1 - z_k) M^{tax} \quad \forall\, k \in K s \in S, f \in F \tag{6c}$$

$$c^{tax} = \sum_k \Delta^{tax} 2^{(k-1)} z_k \tag{6d}$$

The constraints above allow us to replace the bilinear terms $\sum_t W_t E_r^{co2} c^{tax} g_{rstf}$ with the expression: $\sum_k \Delta^{tax} 2^{(k-1)} \hat{g_{ksf}}$. We thus introduce the following expression to replace (5a):

$$\begin{aligned} &\sum_t W_t \sum_r C_{rf}^{var} g_{rtsf} + \sum_k \Delta^x 2^{(k-1)} \hat{g_{ksf}} \\ &+ \sum_t W_t \sum_l C_l^{DR} y_{ltsf} = \sum_t \lambda_t D_t - \sum_r \pi_{rsf} x_r \quad \forall\, s \in S, f \in F \end{aligned} \tag{7a}$$

Next, to linearize the bilinear term $\sigma_r x_r$ in (4a) and (1b), we discretize the subsidy variable σ_r by introducing the following constraints, where Δ^{itc} is a chosen subsidy step size, $j \in K^{itc}$ are discretization intervals, and z_{rj}^{itc} are binary variables:

$$z_{rj}^{itc} \in \{0,1\} \quad \forall\, r \in R, j \in K^{itc} \tag{8a}$$

$$0 \leq \hat{x_{rj}} \leq z_{rj}^{itc} M^{itc} \quad \forall\, r \in R, j \in K^{itc} \tag{8b}$$

$$0 \leq x_r - \hat{x_{rj}} \leq (1 - z_{rj}^{itc}) M^{itc} \quad \forall\, r \in R, j \in K^{itc} \tag{8c}$$

$$\sigma_r = \sum_j \Delta^{itc} 2^{(j-1)} z_{rj}^{itc} \tag{8d}$$

We can now replace the bilinear terms $\sigma_r x_r$ in (4a) and (1b) with the expression: $\sum_j \Delta^{itc} 2^{(j-1)} \hat{x_{rj}}$. We thus introduce the following expression (9a) and (9b) to replace respectively (4a) and (1b).

$$\Omega\Big[\sum_s\sum_f P_{sf}\sum_r \pi_{rsf}x_r - \sum_r C_r^{inv}x_r + \sum_r C_r^{inv}\sum_j \Delta^{itc}2^{(j-1)}\hat{x_{rj}}\Big]$$

$$+ (1-\Omega)\Big[\tilde{\zeta}_r - \frac{1}{\Psi}\sum_s\sum_f P_{sf}u_{rsf}\Big] = 0 \qquad (9a)$$

$$\tilde{u}_{sf} \geq \tilde{\zeta} - \sum_r \pi_{rsf}x_r + \sum_r C_r^{inv}x_r - \sum_r C_r^{inv}\sum_j \Delta^{itc}2^{(j-1)}\hat{x_{rj}} \quad \forall\, s \in S, f \in F \qquad (9b)$$

2.1.6 Bilevel model as a Mathematical Program with Equilibrium Constraints (MPEC)

We can now reformulate our bilevel problem into a single-level optimization problem in the form of a Mathematical Program with Equilibrium Constraints (MPEC)[7]. This is done following the standard approach, which introduces the necessary and sufficient conditions of the lower-level problems (in our case, those belonging to investors and the ISO) as constraints in the upper-level problem (in our case, the government's problem) (Gabriel et al., 2013; Wogrin et al., 2020). This results in the following optimization problem, which represents the government's problem, as represented by its objective function and constraints (10b), subject to the necessary and sufficient conditions of the investor, (10c), and the ISO, (10d). This problem forms a Mixed Integer Quadratically Constrained Program (MIQCP), due to the remaining bilinear terms $\pi_{rsf}x_r$ in (7a), (9a), and (9b) and the mentioned binary variables. Attempts to linearize the remaining bilinear terms $\pi_{rsf}x_r$, which were mentioned in Dimanchev et al. (2024), did not improve the computational speed in our tests relative to solving the MIQCP in Gurobi, which uses McCormick relaxation and spatial Branch and Bound to handle the problem. Additional information regarding the numerical solution is provided in the supplementary document (Section S5).

$$\min_{\alpha} \;\; (3a)\;\big[\text{Risk-adjusted system cost}\big] \qquad (10a)$$

$$\text{s.t.} \;\; (3b)-(3f)\;\big[\text{Government constraints}\big] \qquad (10b)$$

$$(4b)-(4j)(1c)-(1e),(8),(9)\;\big[\text{Investor optimality conditions}\big] \qquad (10c)$$

$$(5b)-(5l),(6),(7)\;\big[\text{ISO optimality conditions}\big] \qquad (10d)$$

The decision variables are in set $\alpha = (\alpha^{gov}, \alpha^{inv}, \alpha^{iso}, \alpha^d)$, where α^d includes all dual variables of the lower-level problems (1) and (2). Thus the decision variables of (10) contain the decision variables of all agents. This makes our model an optimistic bilevel problem. This implies that if the lower-level problem has multiple solutions, our model

[7] The specific approach we take has also been referred to as a Mathematical Program with Primal and Dual Constraints (Tanaka et al., 2022).

will return the one that optimizes the government's objective. Thus, in theory, there is a possibility that the chosen policies can result in different government objective values. We introduce a numerical procedure to test for this in the supplementary document (Section S1); though we find multiple lower-level equilibria in some cases, we confirm that our conclusions are directionally robust across equilibria. Another simplification implied by the formulation of (10) is that the government chooses its policy with full knowledge of how the follower agents will react. While this assumption is not realistic in practice, it allows us to model an ideal benchmark for the optimal policy.

2.2 Bilevel model with complete long-term markets (benchmark)

To assess the effects of missing markets, we construct a benchmark bilevel model with complete risk trading. The difference between this benchmark model and our main model above is in the lower level formulation, which represents a power market with complete risk trading between risk-averse investors and consumers.

2.2.1 Complete market optimization model (lower-level)

A power market with complete risk trading can be modeled as the cost-minimization problem of a risk-averse central planner as shown by Munoz et al. (2017). Risk aversion is again modeled using CVaR, which implicitly captures the risk preferences of market participants and is parameterized using the same values Ω and Ψ used above. The objective function includes both investment cost (subject to the subsidy σ_r) and a weighted combination of expected operating cost (first bracketed term) and the CVaR (second bracketed term). The constraints closely resemble the ISO problem (2), as they feature the same dispatch constraints. The remaining constraints (11c)-(11e) form the CVaR, which represents the Ψ-worst tail of operating costs, following the standard approach (Rockafellar and Uryasev, 2002; Munoz et al., 2017).

$$\min_{\alpha^{cp}} \sum_r (1-\sigma_r) C_r^{inv} x_r + \Omega \Big[\sum_s \sum_f P_{sf} \Big[\sum_t W_t \sum_r C_{rf}^{var} g_{rtsf} + \sum_t W_t \sum_l C_l^{DR} y_{ltsf}$$
$$+ \sum_t W_t \sum_r E_r^{co2} c^{tax} g_{rtsf} \Big] \Big] + (1-\Omega) \Big[\zeta^{cp} + \frac{1}{\Psi} \sum_s \sum_f P_{sf} u_{sf}^{cp} \Big] \quad (11a)$$
$$\text{s.t.} \quad (2b) - (2o) \ \big[\text{Primal dispatch constraints}\big] \quad (11b)$$
$$u_{sf}^{cp} \geq 0 \quad \forall\, s \in S, f \in F \quad (11c)$$
$$\zeta^{cp} \in \mathbb{R} \quad (11d)$$
$$u_{sf}^{cp} \geq \sum_t W_t \sum_r g_{rtsf} C_{rf}^{var} + \sum_t W_t \sum_l C_l^{DR} y_{ltsf} + \sum_t W_t \sum_r E_r^{co2} c^{tax} g_{rtsf} - \zeta^{cp}$$
$$\forall\, s \in S, f \in F \quad (\theta_{sf}^{cp}) \quad (11e)$$

Below, we combine this model with the government problem (3) to form a bilevel problem. As before, our first step is to derive the primal-dual version of the complete market problem (11).

2.2.2 Primal dual reformulation of lower-level complete market model

We derive the primal-dual formulation of the complete market problem (11), which is necessary and sufficient since (11) is a linear program, and discretize the policy variables as above.

$$\sum_r (1-\sigma_r) C_r^{inv} x_r + \Omega \Big[\sum_s \sum_f P_{sf} \Big[\sum_t W_t \sum_r C_{rf}^{var} g_{rtsf} + \sum_t W_t \sum_l C_l^{DR} y_{ltsf}$$
$$+ \sum_k \Delta^x 2^{(k-1)} g_{\hat{k}sf} \Big] \Big] + (1-\Omega) \Big[\zeta^{cp} + \frac{1}{\Psi} \sum_s \sum_f P_{sf} u_{sf}^{cp} \Big]$$
$$= \sum_s \sum_f \sum_t \lambda_{tsf} D_{ts} - \sum_s \sum_f \sum_t \sum_l N_l^{DR} D_{ts} \gamma_{ltsf} \tag{12a}$$
$$(11b) - (11d) \ \big[\text{Primal constraints}\big] \tag{12b}$$
$$u_{sf}^{cp} \geq \sum_t W_t \sum_r g_{rtsf} C_{rf}^{var} + \sum_t W_t \sum_l C_l^{DR} y_{ltsf} + \sum_k \Delta^x 2^{(k-1)} g_{\hat{k}sf} - \zeta^{cp}$$
$$\forall\, s \in S, f \in F \quad (\theta_{sf}^{cp}) \tag{12c}$$
$$(6), (8) \ \big[\text{Linearization expressions}\big] \tag{12d}$$
$$(5b) - (5e), (5h) - (5k) \ \big[\text{Dual dispatch constraints}\big] \tag{12e}$$
$$(\Omega P_{sf} + (1-\Omega)\theta_{sf}^{cp})(W_t C_{rf}^{var} + W_t c^{tax} E_r^{co2})$$
$$- \lambda_{tsf} + \mu_{rtsf} \geq 0 \quad \forall\, r \in G, t \in T, s \in S, f \in F \tag{12f}$$
$$(\Omega P_{sf} + (1-\Omega)\theta_{sf}^{cp}) W_t C_l^{DR} + \gamma_{ltsf} - \lambda_{tsf} \geq 0$$
$$\forall\, l \in L, t \in T, s \in S, f \in F \tag{12g}$$
$$\frac{1}{\Psi} P_{sf} - \theta_{sf}^{cp} \geq 0 \quad \forall\, s \in S, f \in F \tag{12h}$$
$$\sum_s \sum_f \theta_{sf}^{cp} = 1 \tag{12i}$$
$$(1-\sigma_r) C_r^{inv} - \sum_s \sum_f \pi_{rsf} \geq 0 \quad \forall\, r \in R \tag{12j}$$

where (12a) is the strong duality condition of problem (11). Expressions (12b) and (12c) represent the primal feasibility constraints. (12c)-(12d) feature the linearization of the bilinear carbon tax and subsidy terms introduced previously. Expressions (12e)-(12j) represent the dual feasibility constraints.

2.2.3 Benchmark bilevel model MPEC version (complete markets)

We can now convert the bilevel problem comprising the government's problem (3) and the complete market problem (11) into the single-level optimization problem (13). This problem is an MPEC where the government's problem features in the objective and constraint (13b), and the complete market problem is represented by (13c). All decision variables are included in set $\alpha^b = (\alpha^{gov}, \alpha^{cp}, \alpha^e)$, where α^e contains all dual variables of problem (11). The problem represents a Mixed Integer Linear Program (MILP).

$$\min_{\alpha^b} \quad (3a) \ \big[\text{Risk-adjusted system cost}\big] \tag{13a}$$

$$\text{s.t.} \quad (3b) - (3f) \ \big[\text{Government constraints}\big] \tag{13b}$$

$$(12) \ \big[\text{Power market problem with complete markets}\big] \tag{13c}$$

2.3 Experimental setup

To explore the implications of the missing market problem for optimal policy, we compare two cases: a "missing market" case with no long-term contracts between investors and consumers, generated using model (10), and a "complete market" case, generated using model (13). The missing market case is a significant simplification as real-world markets feature some, even if incomplete, trading of long-term contracts (de Maere d'Aertrycke et al., 2017). By comparing this case to the complete market case, we merely aim to indicate the possible directional impact of incomplete markets.

We model an abstract power system with the following technologies: combined cycle gas turbine (CCGT), gas with Carbon Capture and Storage (CCS), onshore wind, solar, 4-hour Li-ion batteries. Unless otherwise indicated, technology parameters are sourced from Dimanchev et al. (2024), who used costs from NREL (2022). The assumed technology costs are provided in the supplementary document (Table S1). The CCS power plant represents the zero-emission CCS technology[8] modeled in Ricks et al. (2024), from where we source the plant's parameters including investment cost and heat rate. The gas price is assumed to be \$3.8/MMBtu (EIA, 2022). The annualized investment costs C_r^{inv} are computed from the CAPEX (Table S1) using a risk-free rate of 2%; additional risk is endogenously captured by our model, as shown in Dimanchev et al. (2024).

Hourly renewable availability and demand are taken from previous modeling for the New England power system (Dimanchev et al., 2021). Here we condense these time series into 14 representative days (thus featuring 336 representative hours) using the k-means clustering algorithm in the GenX open-source model (MIT Energy Initiative and Princeton University ZERO lab, 2023). Stylized demand flexibility parameters are sourced from the example system in the GenX model. We thus include four demand

[8]While a 100% capture rate may be difficult to achieve in practice, this assumption is only of limited relevance to our analysis, as our most ambitious emissions target falls short of full decarbonization.

segments l with costs C_l^{DR} of \$400, \$1,100, \$1,800, and \$2,000 per MWh, with each segment size limited to a total demand reduction N_l^{DR} respectively equal to: 0.3%, 2.4%, 4%, and 100% of total demand.

We represent future uncertainty in demand and the gas price. Demand stochasticity is modeled using two demand scenarios, denoted $s \in S$ that shift demand in each hour by +25% and -25% relative to projected demand (Dimanchev et al., 2021). Similarly, gas price uncertainty is modeled using two scenarios, denoted $f \in F$ where the assumed price is varied by +/-25%. All scenarios, $S \times F$, are assumed to be equally probable. Risk aversion is parameterized for illustrative purposes with $\Omega = 0.5$ and $\Psi = 0.25$. From a generation investor's standpoint, Ω can be seen as the fraction of financing provided by risk-neutral equity investors, and $1 - \Omega$ as the fraction provided by risk-averse debt investors (Mays and Jenkins, 2023). Our choice of $\Psi = 0.25$ implies that risk-averse investors focus on the single worst scenario (since each of the four scenarios has a 25% probability).

3 Results

3.1 Power system outcomes without policy

To set the stage for our analysis, we first consider the power system outcomes in the absence of policy in both the missing market and complete market cases. We observe that CO_2 emissions are higher when long-term markets are missing: expected emissions equal 17 Mt and 10 Mt respectively in the missing markets and complete markets cases. This is because an absence of long-term markets distorts the investment mix away from wind and solar (shown in Figure 3), which leads to an increase in gas generation. This effect is in line with prior work where it is explored in more detail (Dimanchev et al., 2024). Across scenarios, emissions are highest in the two scenarios featuring high demand (and either a high or low gas price), where emissions equal 26 Mt and 17 Mt in the missing markets and complete markets cases respectively.

Our measure of social welfare is lower in the missing markets case relative to the case of complete markets, as expected. Recall that we measure changes in social welfare using the risk-adjusted system cost, which is the objective function of the government agent, (3a). The risk-adjusted system cost is roughly 4% higher in the missing markets case than in the complete market case.

3.2 Optimal policy choices with missing markets

We now consider how a government can use policy instruments to meet a given emissions target. For illustrative purposes, we consider a range of CO_2 targets from 15 Mt to 1 Mt. A target is defined such that emissions cannot exceed a given level in any future scenario (via constraint (3b)). Thus, even the least stringent target of 15 Mt will be binding in both the complete markets and missing markets cases.

The policies we consider are ITC subsidies and a carbon tax, which are modeled one at a time. Figure 2 displays the optimal policy levels across our cases. ITC subsidies (panel a) represent a fraction of a technology's investment cost. We focus on subsidies for wind and solar, thus leaving ITCs for storage or CCS for future work.

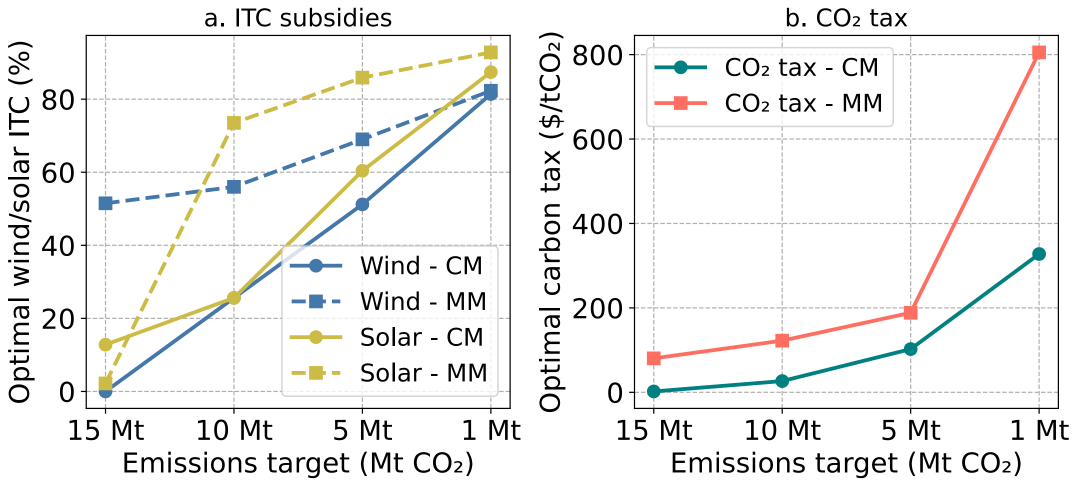

Figure 2: Implications of missing risk markets for optimal policy
CM: complete markets; MM: missing markets; ITC: investment tax credit

We observe in Figure 2-a that it is optimal for the policy maker to implement higher ITC subsidies in the missing markets case than in the complete markets case. The reason for this can be traced to our previous observation that missing markets discourage investment in wind and solar. The government would thus optimally choose to raise subsidies to compensate for the effect of missing markets. We also find in Figure 2-b that the optimal carbon tax increases with missing markets, in line with our results above.

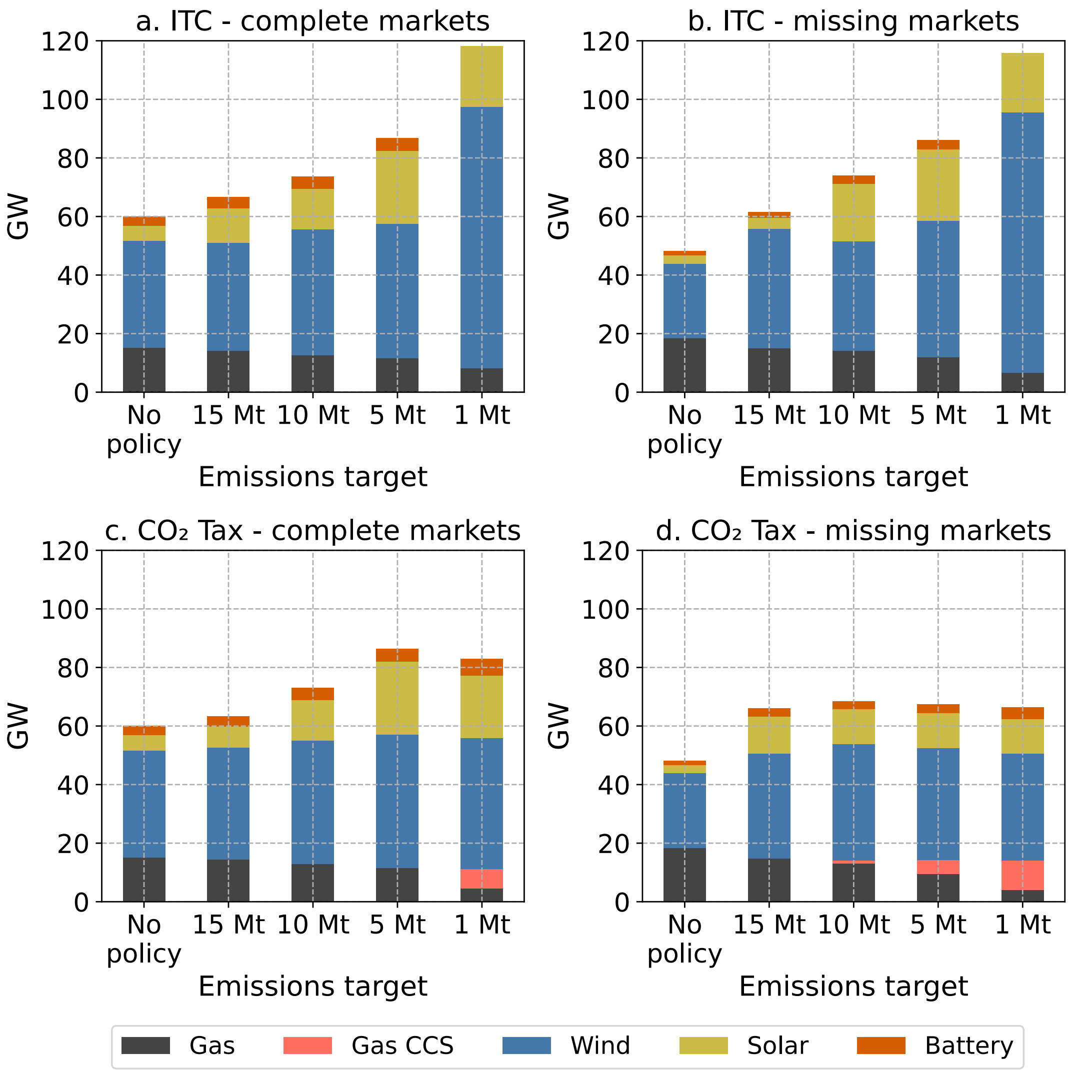

Figure 3: Technology mixes with Investment Tax Credits (ITC) and CO_2 tax

To better understand the effects of the ITC and the carbon tax, we explore the capacity mixes resulting from each policy. When the government uses the ITC policy to decarbonize the power system, the capacity mix is heavily reliant on wind and solar (Figure 3-a/b). Remarkably, storage is no longer deployed at the 1 Mt emissions target. Any remaining net load (i.e., demand net of renewable generation) is more cheaply supplied with gas plants[9], and the government has no policy instrument to incentivize storage investment. In contrast, a carbon tax sends a technology-neutral signal, which incentivizes storage and gas with CCS as well as renewables. (Figure 3-c/d). It is also worth noting that the level of storage investment depends on factors not included in this model including: grid constraints, thermal generator unit commitment constraints, and ancillary

[9]If decarbonization was achieved through more commonly modeled policies, such as emissions constraints and clean energy standards, the gas plant would incur an additional cost through the shadow prices generated by these constraints, which would incentivize more storage investment than under the ITC policy we model here.

service markets. If these market features were included in the model, we conjecture that storage capacity would be higher across our cases than indicated by the results here.

3.3 Policy cost-effectiveness comparison

This section compares the cost-effectiveness of the optimal ITC and the optimal carbon tax. Cost-effectiveness is defined here as achieving a given emissions target at the lowest risk-adjusted system cost. Figure 4 displays the risk-adjusted system cost resulting from each policy.

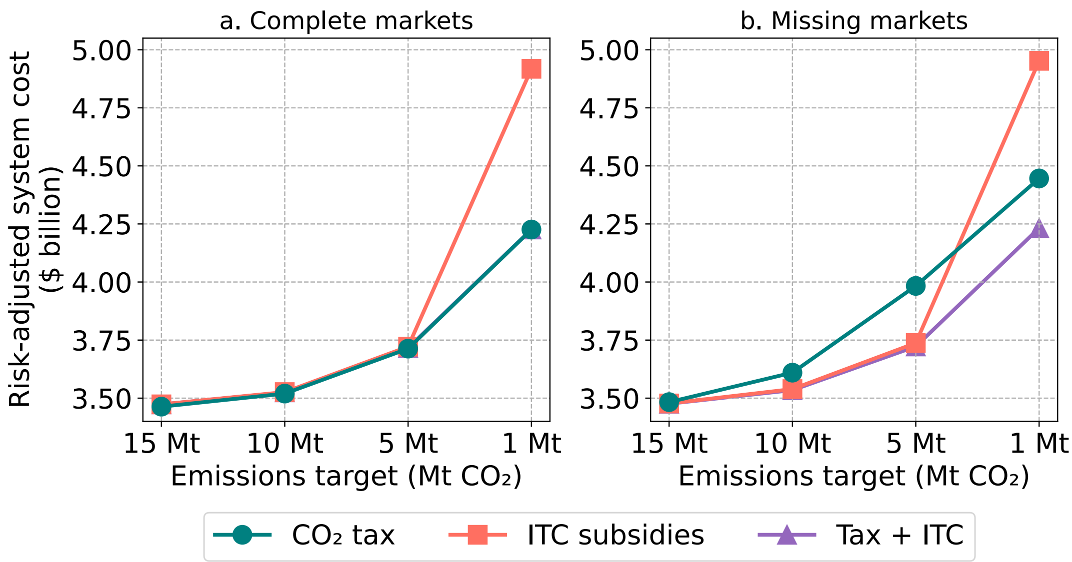

Figure 4: Welfare implications of Investment Tax Credits (ITC) vs. CO_2 tax

We first confirm that, when markets are complete (Figure 4-a), a carbon tax reduces emissions at the lowest cost across our cases. In particular, for an emissions targets of 1 Mt CO_2, the carbon tax leads to a lower risk-adjusted system cost relative to the ITC subsidies. This is driven by the fact that the wind and solar ITC policy fails to incentivize investments in the CCS technology (as shown in Figure 3-a). At levels of deep decarbonization, adding small shares of gas with CCS, which is assumed to be fully flexible, is more cost-effective than additional renewable capacity in our case study power system, in line with previous literature (Sepulveda et al., 2018). In contrast to the renewable ITCs, the carbon tax provides a technology-neutral investment signal, which incentivizes CCS deployment (Figure 3-c).

We also observe in Figure 4-a that optimal wind and solar ITCs are as cost-effective as a carbon tax for the intermediate emissions targets of 15, 10, and 5 Mt. This showcases that wind and solar deployment is a relatively cost-effective decarbonization strategy, but is also due to our experimental set-up. The reasons for the equivalence in system costs is further discussed in the supplementary document (Section S2).

A more striking result is that an absence of risk markets (Figure 4-b) can change the relative cost-effectiveness of climate policies. At the intermediate levels of decarbonization of 10 Mt and 5 Mt, wind and solar ITCs are more cost-effective than a carbon tax. These results reflect the theory of second best: the policy that is optimal in a first-best world (as in our complete markets case) may no longer be the optimal policy in a second-best world (as in our missing markets case) (Lipsey and Lancaster, 1956). The reasons for this difference is explored in detail in Section 3.4. In Figure 4-b, we also observe that, at the 1 Mt decarbonization level, the ITC is less cost-effective than the carbon tax. This is for the same reason as in the complete markets case: the ITC does not incentivize cost-effective abatement through the CCS technology.

We test the sensitivity of the relative cost-effectiveness of ITCs to the level of risk aversion. For the 5 Mt emissions target, the risk-adjusted system cost is 6% lower with ITCs relative to the carbon tax (Figure 4-b). This cost advantage reduces from 6% to 4% for $\Omega = 0.7$ (i.e., lower risk aversion than our main assumption of $\Omega = 0.5$) and disappears for $\Omega = 0.9$ (where system costs are equivalent). For $\Omega = 0.3$ (higher risk aversion), the difference between the two policies is also 6%, showcasing that relative cost-effectiveness does not necessarily scale linearly with the degree of risk aversion.

The differentiated impacts of the two policies lead us to consider how a policy mix will perform. We thus test a policy portfolio combining both a carbon tax and ITC subsidies[10] (Figure 4-b). The results show that the policy mix is more cost-effective than either of the individual policy instruments when risk markets are missing. The policy mix both incentivizes cost-effective CCS deployment at the 1 Mt emissions target (leading to lower costs than the ITC policy alone), and matches the cost-effectiveness of the ITC at less stringent emissions targets (leading to lower costs than the carbon tax alone). The capacity mix in this case is shown in the supplementary document (Section S3).

3.4 Reasons underlying differences in cost-effectiveness

To explore the cost differences between policies in more detail, we distinguish between the costs incurred in each scenario (for any given emissions target case) in Figure 5. Each marker represents the total costs (comprised of investment and operating costs) in a given scenario[11]. The figure also shows, in circle markers, the overall risk-adjusted system cost (i.e., the government's objective function) shown previously in Figure 4.

[10] The policy mix is modeled by allowing the government agent in our bilevel model to choose any level of either instrument, σ_r and c^{tax} to minimize risk-adjusted system cost subject to the emissions target.

[11] Formally each marker represents the value of expression: $\sum_r C_r^{inv} x_r + \sum_t W_t \sum_r C_{rf}^{var} g_{rtsf} + \sum_t W_t \sum_l C_l^{DR} y_{ltsf}$.

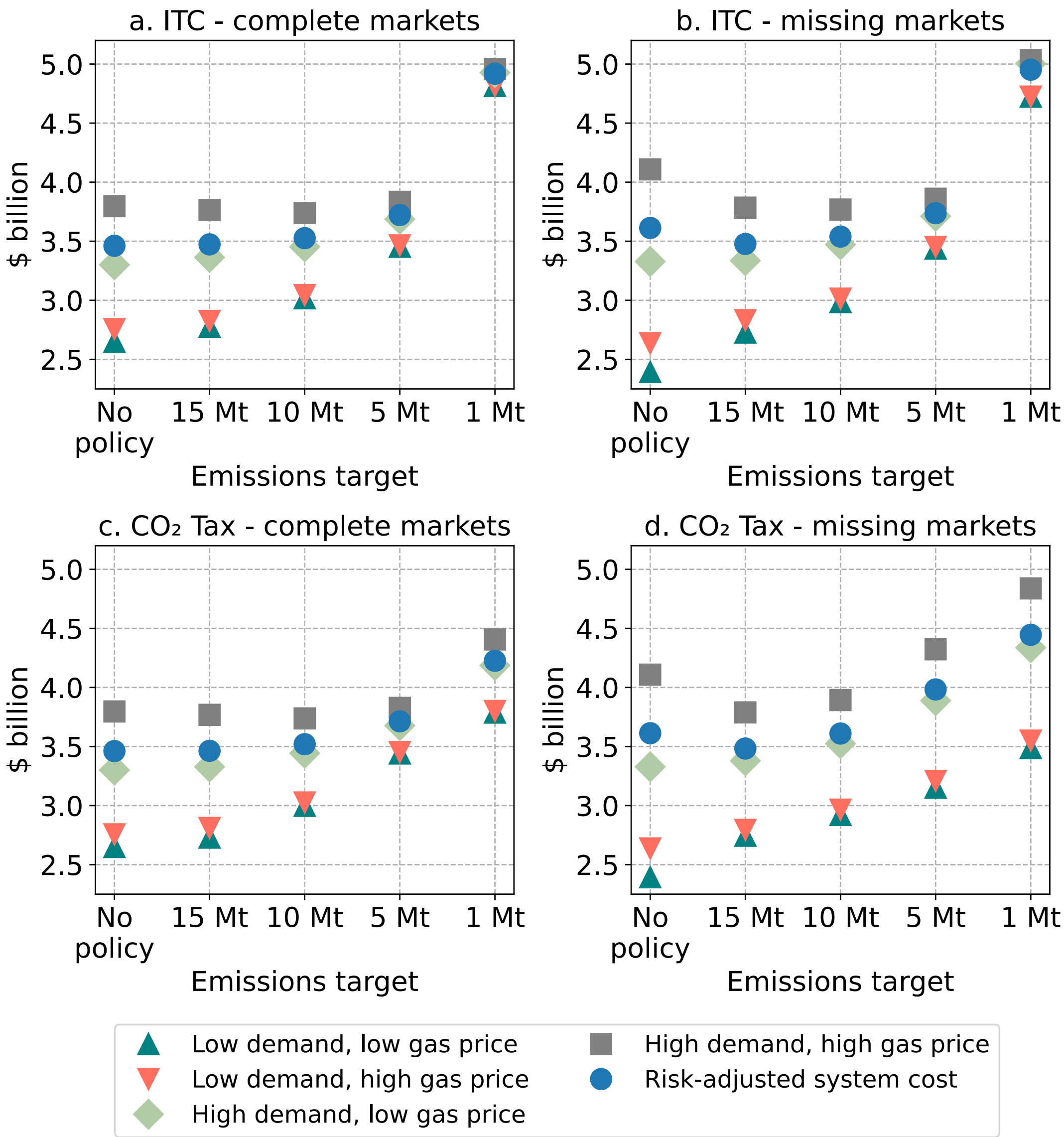

Figure 5: Costs by scenario and overall risk-adjusted system cost with Investment Tax Credits (ITC) and CO_2 tax

We find that overall power system risk differs depending on whether the government uses a carbon tax or ITC subsidies. Risk is quantified here with CVaR, which in our case implies that decision makers put more weight on the worst scenario. Since we measure welfare from the standpoint of a cost-minimizing government agent, the worst scenario is the highest-cost one, which is the "high demand, high gas price" scenario for both the tax and ITC policies (square markers in Figure 5). This scenario has a disproportionate impact on the risk-adjusted system cost, which weights this scenario by 62.5% and the three other scenarios by 12.5% (as reflected by the proximity of the circle and square markers), which is due to the parameterization of the government objective function[12].

[12] In particular, the scenario probability $P_{sf} = 0.25$, the CVaR tail probability level $\Psi = 0.25$, and the degree of risk aversion $\Omega = 0.5$.

In the missing market case, the cost of the highest-cost scenario is lower under the ITC policy (Figure 5-b) than under the carbon tax in the 10 Mt and 5 Mt target cases (Figure 5-d). This is primarily because the greater investment in renewables under the ITC policy decreases gas generation costs relative to the carbon tax case, where there is a higher reliance on gas (Figure 3). Thus, the tail risk of high power system costs is lower with the renewable subsidies than with the carbon tax. These results indicate that ITC subsidies can provide a risk mitigation benefit in power systems with missing risk markets.

It is also worth noting that both climate policies can be economically beneficial when risk markets are missing. Figure 5-b shows that, in the missing markets case, the risk-adjusted system cost is lower under the 15 Mt and 10 Mt targets relative to "no policy". Similarly to our discussion in the preceding paragraph, this is because ITC subsidies mitigate overall risk exposure by reducing the cost of the most costly scenario (with high demand and gas prices). These result imply that the government would optimally prefer to implement some ITC subsidies even if it did not aim to reduce emissions. We confirm that this is the case by re-running our model without an emissions target. Thus, in the missing markets case, the government would choose to implement both wind and solar ITCs purely for the purpose of improving social welfare as expressed by the risk-adjusted system cost. Figure 5-d similarly shows that, under a carbon tax, the risk-adjusted system cost is lower under the 15 Mt target relative to "no policy".

4 Conclusions

Analyses of climate policy have primarily studied the optimal first-best instrument, carbon pricing, for economies without market failures (Pollitt et al., 2024). Here, we present a new approach to modeling optimal climate policy that allows us to both analyze policies beyond carbon pricing and to capture an inefficiency in electricity markets known as the missing market problem. By leveraging bilevel programming, we analyze the optimal choice of renewable subsidies, such as those in the U.S. Inflation Reduction Act. This allows us to explore how optimal subsidies would change in a second-best world with missing risk markets. In illustrative experiments, we observe that optimal ITC subsidies for wind and solar, as well as optimal carbon pricing, are higher in the absence of long-term risk markets.

Our analysis highlights a rarely considered channel through which climate policy can benefit the economy. When risk trading is incomplete, electricity producers and consumers are exposed to unhedged risk. Renewable subsidies can reduce risk by shifting investment decisions toward renewables, which reduces reliance on uncertain gas generation costs. Carbon pricing can similarly result in risk reduction, but to a smaller degree. This suggests that market incompleteness and the climate change externality may be what Bennear and Stavins (2007) call "jointly ameliorating": policies that address climate change could also partly counteract inefficiencies caused by market incompleteness.

Our main finding is that risk can have important implications for the relative cost-effectiveness of subsidies and carbon pricing. In some of our cases, we observe that renewable subsidies lead to a lower risk-adjusted system cost than carbon pricing when risk markets are missing. This is because subsidies exhibit a relatively pronounced risk mitigation benefit in incomplete markets in our experiments. These results suggest that carbon pricing may not always be the most cost-effective climate policy instrument. It is worth noting that the modeled subsidies imply a substantial budgetary cost, which may become prohibitive at levels of deep decarbonization, in contrast to the revenue generating potential of carbon prices. Balancing these considerations could be achieved through a policy mix combining both subsidies and carbon pricing.

A notable limitation of this work is that the risk aversion of market participants is not empirically calibrated, which means that our results are meant to be illustrative. Another important simplification is that we omit risk sharing between the power market and the broader economy, which would reduce the risk exposure of power market participants. An additional direction for future research is modeling the degree of market incompleteness by explicitly representing the trading of different contracts (Mays and Jenkins, 2023). Also of interest are decomposition techniques that could improve the scalability of bilevel modeling (Siddiqui et al., 2023). The presented bilevel framework could also be used to compare the implications of alternative government objectives and constraints to help inform how policy makers can navigate distributional, environmental, and socio-economic trade-offs.

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Declaration of Interests

None.

CRediT authorship contribution statement

Conceptualization, E.D.; S-E.F.; M.K.; Methodology, E.D., S.A.G., F.P.; Investigation, E.D.; Validation, E.D., S.A.G., M.K. S-E.F., F.P.; Writing – Original Draft, E.D.; Writing – Review & Editing, E.D., M.K., S-E.F., S.A.G., F.P.; Supervision, M.K.; Funding Acquisition, M.K.

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Supplementary Information for "Choosing climate policies in a second-best world with incomplete markets: insights from a bilevel power system model"

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S1 Multiple equilibria test

As mentioned in Section 2.1.6 of the main text, our methodological approach does not rule out the existence of multiple lower-level solutions (i.e., power market equilibria) for a given upper-level decision (i.e., government policy). If there exist multiple lower-level solutions with different upper-level objective values, our model (10) will return the one that optimizes the upper-level objective (i.e., minimizes power system cost), which is also known as an optimistic solution. Here, we devise a test to check whether there are any lower-level equilibria that would result in an upper-level objective value that is worse than what we obtain when we solve our model (10). If such equilibria are found, this would mean that our estimates for the cost of a given policy (in Section 3.3) are biased by the optimistic nature of our model. On the other hand, if no such equilibria are found, this would serve as a validation showing our cost estimates are not sensitive to the possibility of multiple lower-level equilibria. It is worth noting that this test merely explores different lower-level equilibria for a fixed upper-level decision, and does not compute what is known as a pessimistic solution[1], which is beyond our scope.

[1]The pessimistic version of the problem is for governments to choose a policy knowing that lower-level players will act in such a way as to lead to the worst-possible upper-level objective.

The purpose of the procedure is to explore the solution space of our model (10). Our test involves three steps, which entail constructing and solving the new optimization problem (1). First, we constrain the government's policy to the values resulting from solving model (10) for a given case (i.e., for a given emissions target and policy instrument). Second, we turn the government's objective from a minimization to a maximization problem. This allows us to check if any lower-level solutions have higher objective function values than when solving (10) where the government's objective is a minimization function. Third, we reformulate the government's CVaR using information from the main solution derived from (10). This is necessary because the CVaR-related variables ζ^{gov} and u^{gov}_{sf} in (10) are not bounded from above; hence, changing the objective of (10) to a maximization would lead to an unbounded problem. To address this issue, we replace the expression $\zeta^{gov} + \frac{1}{\Psi}\sum_s \sum_f P_{sf} u^{gov}_{sf}$ in the objective function of (10). This expression represents the CVaR, which is the operating costs in the Ψ-worst tail of the distribution of operating costs. Our choice of Ψ implies that this tail consists of only one scenario. This scenario is endogenously determined when solving model (10). Once this scenario is known, we can formulate an equivalent model formulation that avoids the use of the auxiliary variables ζ^{gov} and u^{gov}_{sf}. From the solution of model (10), we observe that the Ψ-worst scenario corresponds to high demand $s = 2$ and a high gas price $f = 2$. Hence, in the government's objective function (10a), we can equivalently replace $\zeta^{gov} + \frac{1}{\Psi}\sum_s \sum_f P_{sf} u^{gov}_{sf}$ with $\sum_t W_t \sum_r C^{var}_{r2} g_{rt22} + \sum_t W_t \sum_l C^{DR}_l y_{lt22}$. Overall, this allows us to use the following MIQCP for the purpose of our robustness test.

$$
\begin{aligned}
\max_{\alpha^m} \quad & \sum_r C^{inv}_r x_r \\
& + \Omega \Big[\sum_s \sum_f P_{sf} \sum_t W_t \sum_r C^{var}_{rf} g_{rtsf} + \sum_s \sum_f P_{sf} \sum_t W_t \sum_l C^{DR}_l y_{ltsf} \Big] \\
& + (1-\Omega) \Big[\sum_t W_t \sum_r C^{var}_{r2} g_{rt22} + \sum_t W_t \sum_l C^{DR}_l y_{lt22} \Big] && \text{(1a)} \\
\text{s.t.} \quad & \text{(10b)-(10d)} && \text{(1b)}
\end{aligned}
$$

where $\alpha^m = (\sigma^*_r, c^{co2*}, \alpha^{inv}, \alpha^{iso}, \alpha^d)$. σ^*_r and c^{co2*} denote respectively the subsidy and carbon tax levels resulting from running the main model (10). We also construct a similar test model corresponding to our benchmark model (13).

The results of this test show that our results are robust to the presence of multiple power market equilibria. We observe some solutions with different system costs than previously found (Figure S1, where the solutions from the test model (1) are labeled "highest cost"). In particular, carbon tax solutions feature different[2] system costs in the 10 Mt and 5 Mt cases with missing markets (panel b). On the other hand, ITC solutions exhibit the same

[2]Where the difference is larger than 0.5%, which is our MIP gap.

system costs across all cases. All solutions in the complete market case (panel a) also have the same system costs. Overall, we find that the differences in system costs between policies are directionally robust across equilibria.

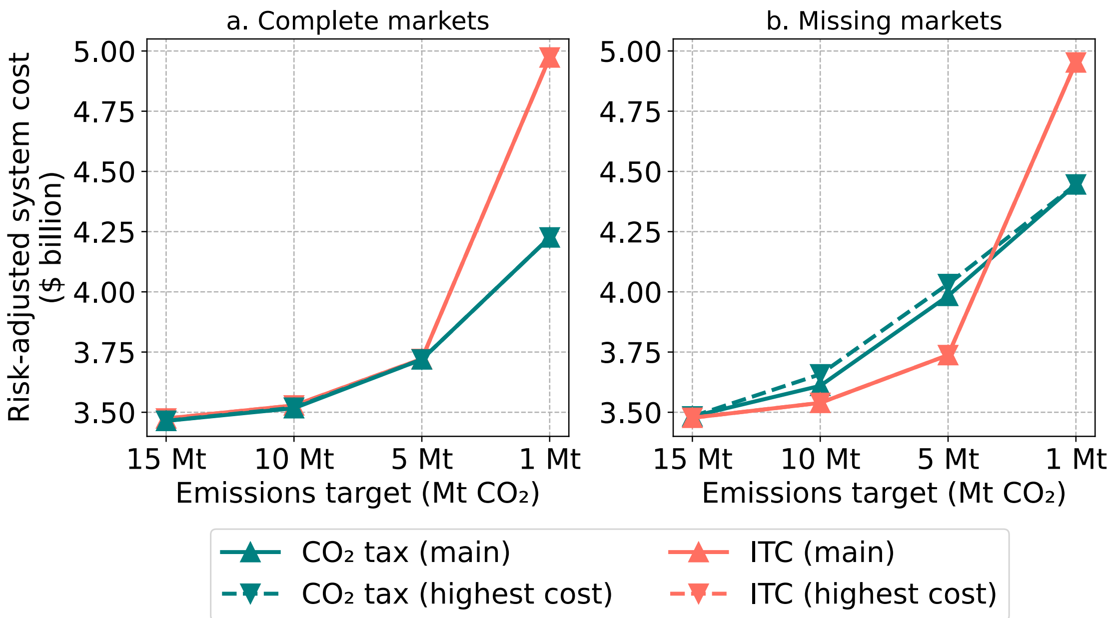

Figure S1: Difference between main estimates and high estimates from multiple equilibria test

S2 Relative cost-effectiveness of ITC subsidies and carbon pricing in complete markets

As discussed in Section 3.3 of the main text, our results show that wind and solar ITC subsidies are as cost-effective as a carbon tax at intermediate decarbonization levels in cases with complete risk trading. This may appear surprising since carbon pricing would generally be expected to be a more cost-effective instrument. The result is partly driven by our omission of other emitting technologies, such as coal, which precludes carbon pricing from driving cost-effective emission reductions via fuel switching from coal to gas. Carbon pricing can also be expected to drive efficient emission reductions via demand reduction (Holland et al., 2009). Focusing on the 5 Mt target case, we observe that, under our assumptions, the carbon tax does not lead to more demand reduction than the ITC. To test the sensitivity of this result, we increase demand flexibility. Our test assumes that 5% of demand can be reduced at a cost of \$50/MWh and another 5% can be reduced at a cost of \$100/MWh (as opposed to 0.4% at \$400/MWh and 2.4% at \$1,100/MWh as otherwise assumed). The results show more demand reduction with the carbon tax, as would be expected. However, the difference in the risk-adjusted system cost is relatively small: we observe a 0.2% lower cost under the tax than under the ITC in this sensitivity test.

S3 Technology investments with ITC + CO_2 tax policy mix

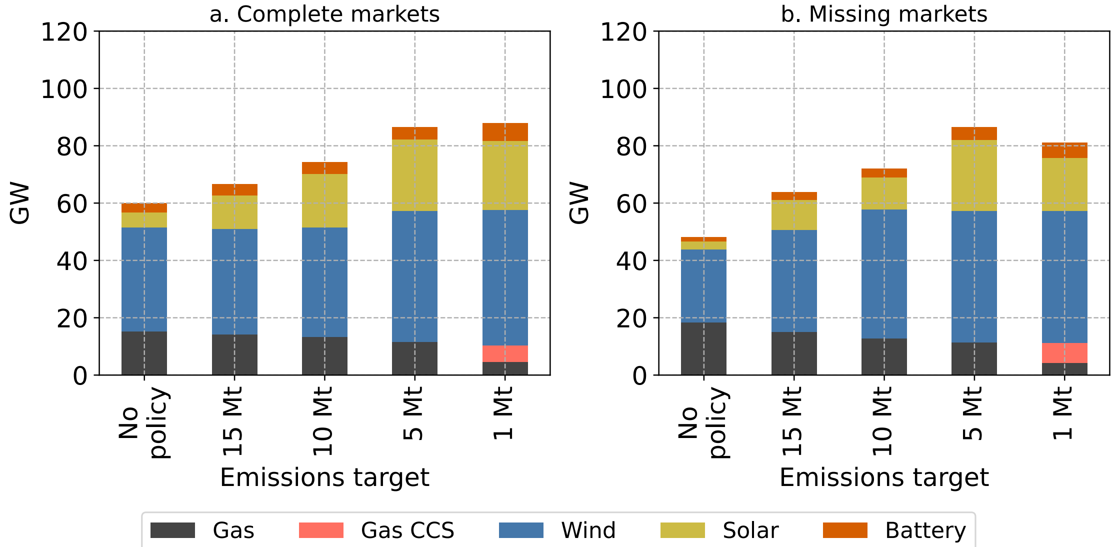

Figure S2: Technology mix

S4 Assumed technology parameters

	CAPEX ($/kW)	Annualized investment cost ($/kW-yr)	Variable cost ($/MWh)	Emissions intensity (tCO_2/MWh)
Gas	912	41	26	0.4
Gas CCS	2,419	108	36	0
Onshore wind	950	42	0	0
Solar	752	34	0	0
Batteries (4-hour)	680	42	0	0

Table S1: Technology parameters

S5 Numerical information

We solve our main model (10), which as discussed forms a MIQCP, with Gurobi's non-convex solver (Gurobi, 2020). We also use Gurobi to solve our benchmark model (13), which forms a MILP. All cases were solved using Gurobi v11.0.0 on a cluster with 48-core Intel(R) Xeon(R) 2.10GHz CPUs and 180GB RAM. We set the ITC step size Δ^{itc} to 0.1% and the tax step size Δ^{tax} equal to \$0.1/tCO_2. To shorten the solution times, we use a MIP gap of 0.5%, so that the government's objective function is solved to a tolerance of 0.5%. Thus, the resulting objective function value is at most 0.5% higher than the global optimal solution. The largest instance of our model, when modeling the ITC, contains approximately 35,000 continuous variables, 54 integer variables, and 20 bilinear constraints (equal to the product of the number of technologies (5) and the number of scenarios (4)). We observed solution times up to 150 minutes.

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